JPAID Journal of Poverty Alleviation and International Development, 6(2)

Micro-determinants of Income Inequality and Consumption in Rural Bangladesh*

Sanzidur RAHMAN**

Abstract: The paper examines the extent to which household and regional characteristics influence income inequality and consumption/welfare based on an in-depth survey of 406 households from 21 villages in three regions of Bangladesh. Results show that the overall Gini coefficient for rural incomes is 0.43 but Gini-decomposition revealed that the contribution of mixed crop production to inequality is just 10 percent while "Green Revolution" technology contributes almost 29 percent. Land ownership, farm capital assets, modern irrigation, non-agricultural income, and household head's education significantly increase consumption. Tenants and households with more dependents are doubly disadvantaged and consume significantly less. Regional factors also significantly influence inequality and consumption. Consumption is significantly higher in regions with developed infrastructure. Comilla is the region with the highest level of inequality and a significantly lower level of consumption. Thus an integrated policy of investments in modern irrigation, crop

---

 The author gratefully acknowledges critical and thoughtful comments from two anonymous referees and the editor which have improved the paper substantially. However, all caveats remain with the author.

** Dr. Sanzidur Rahman is Associate Professor (Reader) in Rural Development with the School of Geography, Earth and Environmental Sciences at the University of Plymouth in the UK. Email: srahman@plymouth.ac.uk

diversification, tenancy reform, mass education and rural infrastructure is necessary to increase consumption/welfare and reduce income inequality in Bangladesh.

Keywords: Income inequality, Gini-decomposition analysis, Consumption or welfare determinants, Bangladesh

Although “eradication of poverty and hunger” has been the main theme of development in the 2000s, the goal remains elusive. However, progress in reducing poverty has been impressive and widespread. The proportion of poor living below the international poverty line (i.e., living under USD 1.25 a day) has fallen to 25.7 percent (or 1.4 billion persons) in 2005 from more than 50 percent in 1981 (or 1.9 billion persons). Nevertheless, there are still large numbers of people living under the poverty line in Sub-Saharan Africa (51 percent), South Asia (40 percent) and East Asia (17 percent) (Krishna 2013), and these figures include two newly emerging economic powerhouses: India and China. Moreover, Krishna (2013) among others argues that policies which were successful in reducing poverty in the past have lost their effectiveness and a business as usual approach is not going to reduce poverty any further.

The importance of non-agricultural income in supporting the livelihoods of rural households in developing countries has been increasingly recognized over the past three decades (e.g., Smith et al. 2001; Deininger & Olinte, 2001; Davis 2004; Hatlebakk 2012). Rural households are commonly involved in diverse income generating activities in order to cope with adverse factors in agriculture (e.g., Ellis 2000; Barrett et al. 2001; Deininger & Olinte 2001; Ellis & Freeman 2004). However, the influence of such diversified livelihood portfolios on inequality is not well known or understood.

Bangladesh is a predominantly agrarian economy in which a large proportion of the population are vulnerable to malnutrition and hunger. Improvements in food security have relied on the extensive use of a rice-based Green Revolution technology (i.e., high yielding varieties of seed, inorganic fertilizers and supplementary irrigation technology) to feed the fast growing population. Consequently, over the past five decades, the major policy focus has been directed towards diffusion of Green Revolution technology aimed at meeting a tripartite objective of increasing food production, generating employment and increasing the income of rural households, all of which complement the national goal of achieving self-sufficiency in foodgrain production and poverty alleviation. It is worth noting that Bangladesh has made considerable progress in improving the wellbeing of its population in recent years. Nevertheless, poverty is still high; 31.5 percent of the population are living below the poverty line (Bangladesh Bureau of Statistics (BBS) 2011).

The degree to which the policy of widely diffusing modern agricultural technology has been successful is contentious in the literature. Several earlier studies based on large-scale sample surveys, for example, Hossain (1989) and Hossain and Sen (1992) find that poverty and inequality is relatively lower in villages with a higher rate of adoption of modern agricultural technology in Bangladesh. However, these studies do not provide evidence of the effects of modern technology inputs specifically. Other country studies attempt to identify the effect of individual inputs. Thapa et al. (1992) showed that the adoption of new technology did not significantly worsen the distribution of income. Rather, it was found to substantially increase the rate of return on land in Nepal. On the other hand, Rahman (2009) noted that the adoption of modern agricultural technology does not seem to have any significant influence on poverty in Bangladesh. In contrast, Benson et al. (2005) noted that agriculture (whether modern or traditional was not specified) is positively associated with poverty in Malawi. Freebairn (1995), after conducting a meta-analysis of 300 studies undertaken during the period 1970–1989, revealed that about 80 percent of these studies concluded that modern agricultural technology widened both inter-farm and inter-regional income inequality. However, he further noted that the authors from Asian countries, who used research data collected in the Philippines and India, concluded that increasing inequality is not associated with modern agricultural technology.

Understanding the precise causes and extent of poverty and inequality has been a major concern of policy makers for some time, and while regional differences exist, research has focussed on a fairly constant set of variables. Particular household characteristics such as education, land ownership, demography and potential sources of income, as well as regional factors such as level of infrastructure development, soil quality and fertility and location, are generally accepted as important influences determining poverty and inequality but with mixed influences. For example, Achia et al. (2010) noted that although education significantly reduces the probability of being poor, rural households are more likely to be poor as compared to their urban counterparts in Kenya. They also noted that demographic factors such as age, religion, ethnicity and region influence poverty. Rahman (2009) noted that while land ownership, farm resource endowments and non-agricultural income significantly reduce the probability of becoming poor, the number of dependants and education of female members has an opposite effect in Bangladesh. Benson et al. (2005) noted the positive influence of education in reducing poverty in Malawi but highlighted that the relationship is somewhat more complex than generally understood. They emphasized increasing access to district level services to address poverty. In contrast, Anyanwu (2005) noted that household size, primary or lower level of education and rural occupation are positively associated with poverty in Nigeria. He also noted feminization of poverty in Nigeria and differential influence of geographic location on poverty. Wodon (2000) noted that education, demographics, land ownership, occupation, and geographic location, all affect poverty in Bangladesh. He further noted that education influences inequality in urban areas while land influences inequality in rural areas. Ravallion and Wodon (1999) also noted that education and regional factors exert significant influence on poverty in Bangladesh.

In sum, previous studies have made clear that modern agricultural technology, demographic, and socio-economic and geographical factors all exert variable influences on poverty. Furthermore, most of the aforementioned studies examined the influence of these various factors on poverty and/or the probability of being poor. Only Wodon (2000) and Ravallion and Wodon (1999) investigated the influence of a wide range of demographic and socio-economic factors on consumption/welfare of Bangladeshi households in urban and rural areas. However, they did not take into account specific impacts of modern agricultural technology adoption and/or cropping portfolio on consumption/welfare of households.

Accordingly, the main objectives of this study are to: (a) estimate the level of income inequality of farming households in selected regions of Bangladesh; (b) identify the sources of income inequality of these farming households; and (c) identify the determinants of consumption/welfare of these farming households. We do so by using an in-depth farm-level sample survey of 406 households from 21 villages in three agro-ecological regions in Bangladesh for the year 1996.

The contributions of our study to the existing literature are as follows. First, it is generally regarded that the value of consumption is a relatively better measure of capturing a household's financial situation than earned income in the context of developing countries because of co-existence of cash and in-kind transactions, lack of record keeping of expenditure and income accounts, and difficulty in deriving net incomes from petty trading and/or business transactions. In this study, we use both type of measures, i.e., income as well as consumption expenditure to address our specified objectives, which is not commonly found in the literature. Second, for countries such as Bangladesh where technological progress in agriculture is deemed to be a pre-requisite for economic growth and development, detailed information on the extent and influence of the adoption of modern agricultural technology is also crucial to any study of inequality.

The paper is organized as follows. The next, second, section presents the methodology and describes the data including region-specific income patterns of the households that make up the sample. The third section presents the results which include contribution of modern agricultural technology to income inequality using Gini decomposition analysis, and identification of the demographic, socio-economic and regional/spatial determinants of consumption/ welfare of these households using a multivariate regression analysis. The final section concludes and draws policy implications.

Methodology

Measures of income inequality and its sources: A Gini-decomposition analysis

One of the most common measures of inequality in income distribution is the Gini-coefficient, which is based on the Lorenz curve. Moreover, the Gini coefficient has a unique underlying social welfare function that is based on the rank of individuals (Makdissi & Wodon 2012). Also, the popularity of the Gini as a measure of inequality is that it can be decomposed by source of income and/or classes (such as region). Some of the best-known papers on Gini decomposition are Rao (1969), Pyatt (1976), Fei et al. (1978) and Pyatt et al. (1980). Yao (1997) noted that the covariance method for Gini decomposition is not appropriate for unevenly grouped populations and proposed an alternative decomposition approach that is exact. In this formulation, the Gini-coefficient for measuring income inequality is given by (Yao 1997):

$$G = 1 - \sum_{i=1}^{n} p_i (2Q_i - w_i) \tag{1}$$

with the relation

$$\sum_{i=1}^{n} p_i = 1, \sum_{i=1}^{n} w_i = 1,\ w_i = \frac{p_i m_i}{m},\ Q_i = \sum_{k=1}^{i} w_k$$

where, n = number of income groups,

m_i=mean income of group i (i−1,2,⋯n),

m = mean income of the entire population,

p_i=population share of group i,

w_i=income share of group i in total income.

Q_i=cumulative income share from group 1 to group i with p_i and w_i following an ascending order of m_i ($m_1 \leq m_2 \leq \cdots \leq m_n$).

If per capita total income is decomposed into F components, then the Gini coefficient for component income is given by:

$$G_f = 1 - \sum_{i=1}^{n} p_i (2Q_{fi} - w_{fi}) \tag{2}$$

with the relation

$$\sum_{i=1}^{n} p_i = 1, \sum_{i=1}^{n} w_{fi} = 1, \; w_{fi} = \frac{p_i m_{fi}}{m_f}, \; Q_{fi} = \sum_{k=1}^{i} w_{fk}$$

where, n = number of income groups,

m_{fi} = mean component income of group I (i=1,2,…n),

m_f = population mean income of component f (f=1,2,…,F),

p_i = population share of group i,

w_{fi} = income share of group i in total income of component f.

Q_{fi} = cumulative income share from group 1 to group i with p_i's and w_{fi}'s following an ascending order of m_{fi}'s ($m_{f1} \leq m_{f2} \leq \ldots \leq m_{fn}$).

Equation 3 can also be used to calculate the component concentration ratio if p_i's and w_{fi}'s follow an ascending order of group mean total income m_i's instead of group mean component income m_{fi}'s as shown below:

$$C_f = 1 - \sum_{i=1}^{n} p_i (2Q_{fi} - w_{fi}) \tag{3}$$

with p_i's and w_{fi}'s following $m_1 \leq m_2 \leq \cdots \leq mn$.

Substitution of equation 3 in 1 provides the decomposition of Gini coefficient as:

$$G = \sum_{f=1}^{F} w_f C_f \tag{4}$$

with the relation

$$\sum_{f=1}^{F} w_f = \sum_{f=1}^{F} \frac{m_f}{m} = 1$$

Equation 7 indicates that Gini coefficient is the weighted average of component concentration ratios. The examination of how each individual component contributes to total income inequality is given by:

$$g_f = \frac{C_f}{G}, \; and \; \sum_{f=1}^{F} w_f g_f = 1 \tag{5}$$

where, g_f= is termed as relative concentration coefficient.

$w_f g_f$= share of component f in the Gini coefficient G.

An income component is said to be inequality increasing if its $g_f > 1$. The implication is that if total income remains unchanged, the increase in the share of a single component will result in an increase in overall income inequality and vice-versa. In this decomposition method the relative contribution of an income component to the Gini coefficient will depend on its share in total income w_f as well as on the value of g_f.

Microdeterminants of consumption: A multivariate regression model

In the previous section, we have developed measures to compute income inequality and relative contribution of various income sources to inequality. But what are the determinants of per capita consumption, an alternative robust measure of inequality that can be analysed using information at the individual household level whereas the Gini index is an aggregate measure which can only be computed for a group of households or region?

We have used "welfare ratios" to measure consumption defined as the household's per capita consumption normalized by the appropriate regional poverty line so that differences in costs of living between regions are taken into account (Wodon 2000). A welfare ratio equal to one indicates that the household has consumption at the level of the poverty line. In other words, if the welfare ratio is below unity, then the household is deemed to be poor. In the conventional measure, binary variables are used to define the poor, which takes the value of 1 for households whose income falls below the poverty line expenditure and 0 otherwise. Such a measure cannot take into account how far a household is below the poverty line expenditure. Our measure is providing a continuous measure of the extent of poverty of the household relative to the poverty line expenditure. A value above unity implies that the household is above the poverty line and shows the extent to which it is above the poverty line expenditure.

Following standard practice, we use the semi-log specification since per capita consumption/welfare ratio (the dependent variable) is not normally distributed (Wodon 2000). The following regression model is specified:

$$\ln Y_i = \beta' X_i + \mu_i \tag{6}$$

The dependent variable is the log welfare ratios, i.e., log of nominal per capita consumption divided by the poverty line of the area in which the household lives (Wodon 2000). The X_i is the vector of regressors, β is the vector of parameters to be estimated, and μ_i is the error term. STATA V10 software is used to estimate the model (StataCorp 2010).

Data

Primary data for the study came from an intensive farm-survey conducted from February to April, 1997, in three agro-ecological regions of Bangladesh. Twenty-one villages were included, eight from the Central sub-district of Jamalpur representing wet agro-ecology areas, six from the Manirampur sub-district of Jessore representing dry agro-ecology areas, and seven from the Matlab sub-district of Comilla, representing wet agro-ecology and agriculturally developed areas. A total of 406 farm households (175 in Jamalpur, 105 in Jessore and 126 in Comilla) were selected from these villages using a multistage stratified random sampling procedure.

To identify the sources of income inequality and consumption determinants, a number of variables were constructed, grouped as follows: sources of income to the household; production inputs; household characteristics; and two indices, one to capture soil quality and the other the degree of local infrastructure development. Regional dummies are also included.

Income: Household or family income is defined as the return to family labor, plus those assets owned after the current cost of production (excluding rent for land and assets) is deducted from the gross value of production (Ahmed & Hossain 1990). Current costs are those incurred by individual households in purchasing inputs, hiring labor and animal power services, and renting services (details of components of income and their derivation is presented in the Appendix). Income from agriculture is separated into income from various crops, fisheries, livestock and lease income from land. This is reported in Table 1. Crop income is the aggregate of that derived from local and modern varieties of rice (all season), wheat, jute, potatoes, pulses, spices, oilseeds, vegetables and cotton. Modern rice varieties account for more than 60 percent of total crop income, while other crops including local varieties of rice contribute very little. For all crops there are sharp inter-regional variations. As indicated in Table 1, Jessore, the region with the more diversified cropping system has the highest income, although this is not the region with the greatest share of modern varieties (Jamalpur for rice and Comila for wheat). Nonetheless, it is clear that for two regions, field crop income is overwhelmingly the dominant source of total household income and in only one region does non-agricultural income appear to be significant.

Table 1.
Structure of Annual Total Income (BDT) Per Household

Source of income	Share of component incomes to total income by region (%)			
	Jamalpur	Jessore	Comilla	All regions
Total agricultural income	84.3	73.3	50.2	72.3
Crops	53.3	44.7	34.6	45.9
Traditional rice	3.9	0.3	3.2	2.6
Modern rice	44.5	26.6	22.6	33.3
Modern wheat	0.6	1.9	2.8	1.6
Jute	0.8	4.8	1.4	2.2
Potato	0.9	0.3	2.9	1.2
Pulses	0.0	3.9	0.2	1.3
Oilseeds	0.1	1.5	1.0	0.8
Spices	2.2	0.1	0.6	1.1
Vegetables	0.3	3.6	0.0	1.3
Cotton	0.0	1.6	0.0	0.5
Livestock	14.9	17.3	13.4	15.3
Fisheries	5.5	5.1	1.1	4.3
Lease	10.6	6.2	1.1	6.8
Total non-agricultural income	15.7	26.7	49.8	27.7
Wage	4.6	3.7	8.6	5.3
Business and other	11.1	23.0	41.2	22.4
Total family income	100.0 (31,581)	100.0 (39,064)	100.0 (25,314)	100.0 (31,571)

Note. Figures in parentheses represent total income per household. Exchange rate USD 1.00 = BDT 81.86 (Bangladesh Bank 2012). Source is Field Survey, 1997.

Poverty line expenditure: The cost of basic needs (CBN) approach is used to construct the region-specific poverty line expenditure (Wodon 2000, 1997; Ravallion & Sen 1996). In constructing the food poverty expenditure as a first step, a cost-minimizing long-term diet set with available food items that attain the recommended nutrition level of 2,112 kcal and 58 grams of protein per capita per day proposed by Mian (1978) is utilized. In addition, expenditure on non-durable goods and/or non-food allowance is estimated at 30 percent of the food poverty line (a standard practice in the context of Bangladesh, e.g., Hossain (1989), Ahmed and Hossain (1990). The region-specific poverty line expenditures are different across regions with an overall estimate of BDT 5,409 per capita per year (see Table 2).

Consumption: Consumption expenditure was constructed using the following procedure. First, quantities of food items consumed (both purchased and home supplied) during seven days prior to the date of interview were converted into values using market prices within the village and then multiplied by 52 weeks to compute annual expenditure on food. Next, monthly expenditure on durable goods, such as, dress/clothing, education, transportation and debt servicing were collected and multiplied by 12 months to compute annual expenditure. Finally, annual expenditure on investment, maintenance of properties, social and religious works was also collected. All these consumption expenditure items were summed and then divided by household size to obtain total nominal consumption expenditure per capita per year. The region-specific actual consumption expenditure, thus constructed, are significantly different across regions (F-statistic = 9.83; $p<0.01$) with an overall estimate of BDT 6,068.6 per capita per year (see lower part of Table 2).

Table 2.
Poverty Line Expenditure Required to Fulfill Nutritional and Other Requirements

Food item	Qty. (gm) of food included in optimal diet	Cost of attaining the optimal diet evaluated at region-specific retail market prices (BDT)			
		Jamalpur	Jessore	Comilla	All regions
Rice	432.6	4.90	4.36	4.46	4.62
Wheat	58.3	0.64	0.58	0.64	0.62
Potato	36.7	0.15	0.14	0.15	0.14
Lentil	25.0	0.53	0.54	0.53	0.53
Fish	38.3	2.11	2.43	2.24	2.24
Meat	1.7	0.11	0.13	0.11	0.12
Milk	31.1	0.48	0.43	0.53	0.50
Dry milk	2.5	0.55	0.55	0.55	0.55
Sugar	27.2	0.70	0.70	0.70	0.70
Oil	12.2	0.70	0.69	0.63	0.68
Onion	8.5	0.09	0.07	0.07	0.08
Non-leafy vege.	86.8	0.38	0.58	0.52	0.53
Leafy vegetable	20.0	0.09	0.09	0.10	0.09
Cost of food per capita per day		11.43	11.29	11.23	11.40
Annual cost of food		4,172.0	4,120.9	4,099.0	4,161.0
Annual cost of non-food items		1,251.6	1,236.3	1,229.7	1,248.3
Poverty line expenditure per year per capita		5,423.6	5,357.2	5,328.7	5,409.3
Actual estimated consumption expenditure per year per capita		6,453.6	6,648.6	5,050.3	6,068.6
Welfare ratios (i.e., consumption expenditure /poverty line expenditure)		1.21	1.24	0.94	1.14

Note. Exchange rate USD 1.00 = BDT 81.86 (Bangladesh Bank 2012). Values are extended from Rahman (2009).

Production inputs: Two land variables were used in the analysis. The amount of land (in hectares) owned per capita is an indication of the wealth of the family, while the area of land under cultivation or farm operation size per household is a direct production input which is made up of owned, rented-in and/or mortgaged-in land. In addition, the value of farm capital assets is included which also serves as production input because it includes the value of livestock resources owned, which is a major source of draft power in farming. Use of land as a determinant is abundant in the literature (e.g., Rahman 2009; Benson et al. 2005; Anyanwu 2005; Wodon 2000; Thapa et al. 1992). Use of farm capital asset is, however, less common in the literature (e.g., Rahman 2009). Both of these variables are assumed to positively influence consumption/welfare.

Cropping portfolios and level of modern technology adoption: These are the proportion of area irrigated (also a major production input particularly for producing high yielding varieties of rice) and the level of cropping diversity. As mentioned earlier, the use of modern agricultural technology to identify its influence on poverty and inequality are important but the results are mixed in the literature (Rahman 2009; Freebairn 1995; Thapa et al. 1992). It is expected that adoption of modern agricultural technology will be income neutral and/or consumption/welfare enhancing.

Household characteristics: These variables were the number of non-working dependents, years of formal education of the head of household and highest education level of any male members, and age of the head (a proxy variable representing experience). Use of these demographic and socio-economic factors is most common in poverty studies (e.g., Rahman 2009; Benson et al. 2005; Anyanwu 2005; Wodon 2000), though there is no consensus on their influences on poverty and inequality. We have used two separate indicators of head's education and highest education of any male members in the household in order to identify the existence of centralized decision making (Asadullah & Rahman 2009) and their corresponding influence on consumption/welfare. We assume that these variables will be consumption enhancing.

Regional/spatial factors: Two indices to capture the influence of spatial factors were included in the analysis. These are: soil fertility and state of infrastructure. The soil fertility index is constructed from test results of soil samples collected from representative locations during a field survey for crop year 1996. Ten soil-fertility parameters were tested, namely soil pH, nitrogen, potassium, phosphorus, sulfur, zinc, texture, exchange capacity, content of organic matter and electrical conductivity. Each of these positive characteristics was assigned 1 point and thus a high index value implies better soil fertility.[1] The infrastructure index was constructed using the cost of access approach. Here thirteen elements are included, namely primary markets, secondary markets, storage facilities, rice mills, paved roads, bus stops, banks, union offices, agricultural extension offices, high schools, colleges, sub-district headquarters and post offices. A high index value implies poorly developed infrastructure.[2] Use of these two indices, although deemed quite important, is not usually reported in the literature with a few exceptions (e.g., Rahman 2009; Anyanwu 2005). We assume soil fertility status and developed infrastructure to have consumption/welfare enhancing effects.

Although the data collected for this study are 18 years old, little has changed with regard to the farming practices and operating institutions over this period in Bangladesh, except for an increase in the level of modern rice technology adoption from 38.6 percent of gross cropped area in 1990 to 62.9 percent in 2011 (Ministry of Agriculture 2008; BBS 2012). Therefore, we argue that our results are capable of providing valuable information of relevance to policy makers and development practitioners alike.

Results

Level of income inequality and its sources

The Gini-coefficients (G and G_f), income shares (w_i and w_{fi}), component concentration ratio (C_f), relative concentration ratio (g_f) and

---

1 For details of the construction procedure of the soil fertility index, see Rahman (1999).

2 For details of the construction procedure of the infrastructure index, see Rahman (1999) and Ahmed and Hossain (1990).

inequality weights ($w_f g_f$) for the income components modern agricultural technology income, other field crop income, non-crop agricultural income, and non-agricultural income classified by region are presented in Table 3.

Table 3.
Measures of Income Inequality and Its Sources

Income components	Per capita income	Share in total income %	Gini coefficient	Concentration ratio	Contribution to total Gini	Relative concentration ratio	Inequality weight %
	m_f	w_f	G and G_f	C_f	$w_f C_f$	$g_f = C_f / G$	$w_f g_f$
Comilla region							
MV technology	1003.5	23.9	0.512	0.156	0.037	0.340	8.1
Other crop	413.7	09.8	0.757	0.409	0.040	0.889	8.7
Non-crop agri.	658.0	15.7	0.513	0.278	0.044	0.604	9.5
Non-agriculture	2129.2	50.6	0.750	0.670	0.339	1.457	73.8
Total income	4204.4	100.0	0.460		0.460		100.0
Jamalpur region							
MV technology	2837.5	45.4	0.464	0.351	0.159	0.887	40.2
Other crop	442.3	07.1	0.746	0.329	0.023	0.829	5.9
Non-crop agri.	2030.0	32.4	0.599	0.463	0.150	1.167	37.9
Non-agriculture	946.8	15.1	0.820	0.425	0.064	1.075	16.3
Total income	6256.6	100.0	0.395		0.395		100.0
Jessore region							
MV technology	1761.6	27.6	0.514	0.353	0.097	0.873	24.1
Other crop	950.8	14.9	0.646	0.457	0.068	1.131	16.8
Non-crop agri.	1835.8	28.8	0.562	0.398	0.114	0.986	28.3
Non-agriculture	1837.2	28.8	0.662	0.431	0.124	1.066	30.7
Total income	6385.4	100.0	0.404		0.404		100.0
All regions							
MV technology	1990.1	35.2	0.534	0.354	0.125	0.817	28.8
Other crop	564.9	10.0	0.737	0.442	0.044	1.019	10.2
Non-crop agri.	1554.0	27.5	0.617	0.459	0.126	1.060	29.1
Non-agriculture	1544.0	27.3	0.757	0.507	0.139	1.170	32.0
Total income	5653.05	100.0	0.433		0.433		100.0

Analysis of the Gini coefficients reveal that the degree of income inequality is highest in Comilla (0.46), lower in Jessore (0.404) and lower still in Jamalpur (0.395). Estimates of Gini indices, based on in-depth farm surveys, are 0.35 for the year 1982 (Hossain 1989) and 0.35–0.37 for the year 1987 (Hossain et al. 1990). The current estimates indicate that inequality has increased over this time period. However, Wodon (2000), using Bangladesh Household Expenditure Survey 1995/96 data, reported an overall rural Gini index of 0.26 instead.

The impact of modern agricultural technology adoption on income distribution is complex. It is evident from Table 3 that the contribution of modern agricultural technology to income inequality is substantial and accounts for 28.8 percent of total inequality (last column) for the regions in aggregate. However, the regions vary in the rate of adoption of these technologies and this is reflected in the extent to which the inequality enhancing effect is apparent. In Jamalpur, where the share of modern technology income is very high (45.4 percent), the contribution to income inequality is also high at 40.2 percent. In comparison, the other two regions have adopted modern technologies on a small scale, and subsequently show a lower impact on their inequality weighting. However, it is encouraging to note that, generally, modern agricultural technology is inequality decreasing as shown by the relative concentration ratio (column 6). This term for the aggregate sample is 0.817 (< 1.00) while other field crop income is neutral (1.019 ~ 1.00). Non-crop agricultural income and non-agricultural income is inequality increasing (1.06 and 1.17 > 1.00) as expected. The implication is that the promotion of modern agricultural technology as well as diversified cropping patterns will reduce income inequality relative to non-crop agricultural and non-agricultural income sources, given that total income remains unchanged.

Microdeterminants of consumption/welfare: A multivariate regression analysis

In the previous section, we have examined the level of inequality and relative contribution of various income sources to inequality. In this section, we examine the determinants of per capita consumption/welfare using the multivariate regression model (Eq. 6).

The explanatory variables included in the model are: per capita land owned (ha); total farm operation size (ha); value of farm capital assets ('000 BDT); modern irrigation (share of cultivated area under modern irrigation); tenancy dummy (1 if tenant, 0 otherwise); Herfindahl index of crop diversity (number); number of dependents in the household (persons); share of non-agricultural income in total income (proportion); education level of household head (completed years of schooling); maximum education level of any male member in the household (completed years of schooling); age (years); index of infrastructure underdevelopment (number); index of soil fertility (number); and regional dummies (Comilla and Jessore). Choice of these variables is based on the literature discussed at length in the Methodology section above.

Result shows that the welfare ratios or consumption expenditures are also significantly different across regions (F-statistic 8.89; $p<0.01$) with an average of 1.14 while for Comilla region, the figure is below one (see last row of Table 2). These welfare ratios are comparable to the one reported by Wodon (2000) estimated at 1.08–1.29 for the rural sector in 1995–1996 based on Household Expenditure Survey data.

The results of the Ordinary Least Squares regression with robust standard error are in Table 4. A large number of coefficients are significant at the one, five or ten percent level. The F-statistic further indicates statistically that these variables contribute significantly as a group to the explanation of the determinants of consumption of rural farm households. About 45 percent of the variation in consumption is explained by these characteristics variables as indicated by the value of the Adjusted R-squared. The null hypothesis of no influence of socio-economic factors jointly on consumption/welfare is strongly rejected at the one percent level. Similarly, the null hypothesis of no influence of geographic/spatial factors jointly on consumption/welfare is also strongly rejected at the one percent level. Coefficients in Table 4 can only provide direction of the influence but not the correct magnitude of influence. Therefore, to obtain a measure of change in consumption/welfare with respect to changes in the characteristics variables, consumption/welfare elasticities at the sample means are estimated and reported in Table 5.

In general, studies investigating the influence of land resources, whether measured as owned or simply land under cultivation, find a positive effect on income levels or input demand. In this study, two variables are used to represent land resources. Intuitively, the major land factor determining income levels and hence consumption will be land owned. Results reveal that land ownership significantly increases consumption/welfare and is the most dominant variable consistent with our expectation. The elasticity value is estimated at 0.14 implying that a one percent increase in land owned per capita will increase consumption by 0.14 percent. Wodon (2000) also reported significant influence of land ownership on consumption in rural areas. Although farm size has no influence on consumption, farm capital assets significantly influence consumption, again consistent with expectation. The implication is that wealth, measured in terms of land ownership and/or capital assets, significantly enhances consumption. This is expected in a land scarce country like Bangladesh where land is a major source of wealth.

Modern irrigation, a major pre-requisite and input for modern agricultural technology, also significantly increases consumption as expected and is the second strongest determinant amongst the socio-economic factors after land ownership, with an elasticity value of 0.07. This is because irrigation opens up opportunities to adopt modern rice technology which provides significantly higher yields than traditional rice, and therefore enhances consumption.

Return to education of the head on consumption is also significant and is the third most dominant variable with an elasticity value of 0.04. The coefficient on the maximum level of education of any member in the household is also positive and significant at the 15 percent level. Wodon (2000) also reported significant returns to education on consumption.

Similarly, Achia et al. (2010) and Benson et al. (2005) noted a significant influence of education on reducing poverty. The implication is that education for members of the household is positively associated with enhancing consumption. The combined influence of these two education variables is 0.09 which means that a one percent increase in educational attainment at the household level will increase consumption by 0.09 percent.

Non-agricultural income source also significantly increases consumption as expected and is consistent with the literature. A one percent increase in non-agricultural income will increase consumption by 0.03 percent. Rahman (2009) also noted a significant poverty reduction influence for non-agricultural income.

Tenants have a significantly lower level of consumption. Bangladesh is an economy where functionally landless households account for over 50 percent of agricultural production units. Since the land rental market is not very effective, generation of income through farming is difficult which ultimately affects consumption adversely. Rahman (2009) also noted that tenants are more likely to be poor.

The number of dependents in the household significantly reduces consumption and the effect is highest with an elasticity value of −0.28. A higher number of dependents exerts pressure on the household with respect to consumption of goods and services which are to be provided by fewer earners. The finding is consistent with those reported in the literature (e.g., Anwanyu 2005).

The regional/location factor also exerts significant influence on consumption. There is a pronounced positive influence of rural infrastructure on consumption. Consumption is significantly higher in developed regions. The elasticity value indicates that a one percent increase in the index of rural infrastructure will increase consumption by 0.13 percent. In general, the developmental effect of infrastructure is indirect and complex (Ahmed & Hossain 1990), although its influence on poverty and inequality is emphasized in the literature. For example, Benson et al. (2005) and Anyanwu (2005) recommended improving access to services to reduce poverty. We have demonstrated that the development of rural infrastructure has a clear positive influence on increasing consumption/welfare of the households. Consumption is significantly lower in Comilla region where inequality is also highest (Table 3).

Table 4.
Microdeterminants of Income Inequality

Variable list	Coefficient	Robust standard errors	z-values
Constant	0.348*	0.217	1.65
Socio-economic factors			
Per capita land owned	1.208***	0.192	6.30
Farm operation size	0.001	0.024	0.01
Farm capital assets	0.002*	0.000	1.67
Herfindahl index of crop diversity	-0.035	0.075	-0.49
Irrigation	0.108*	0.067	1.65
Tenants	-0.117**	0.053	-2.21
Share of non-agricultural income	0.123**	0.059	2.07
Dependents in the household	-0.070***	0.010	-6.90
Education level of household head	0.010*	0.005	1.82
Highest education of male member in the household	0.009	0.006	1.47
Age of the head	0.001	0.001	0.84
Village level factors			
Index of infrastructure underdevelopment	-0.004***	0.001	-2.60
Index of soil fertility	-0.117	0.136	-0.86
Comilla region	-0.175***	0.047	-3.70
Jessore region	-0.043	0.071	-0.61
Model diagnostic			
Adjusted R^2	0.45		
F-statistic $_{(15,390df)}$	25.98***		
H_0: No influence of socio-economic factors on consumption/welfare (F-statistic $_{(8,390df)}$)	25.27***		
H_0: No influence of spatial/geographic factors on consumption/welfare (F-statistic $_{(4,390df)}$)	6.45***		
Number of observations	406		

*** = significant at 1 percent level (p<0.01); ** = significant at 5 percent level (p<0.05); * = significant at 10 percent level (p<0.10).

Table 5.
Consumption/Welfare Elasticities

Variable list	Elasticity estimates
Socio-economic factors	
Per capita land owned	0.135**
Farm operation size	0.001
Farm capital assets	0.012*
Herfindahl index of crop diversity	-0.021
Irrigation	0.067*
Tenants	-0.017**
Share of non-agricultural income	0.027**
Dependents in the household	-0.279***
Education level of household head	0.037*
Highest education of male member in the household	0.054
Age of the head	0.047
Regional/spatial factors	
Index of infrastructure underdevelopment	-0.132***
Index of soil fertility	-0.196
Comilla region	-0.054***
Jessore region	-0.011

*** = significant at 1 percent level ($p<0.01$); ** = significant at 5 percent level ($p<0.05$); * = significant at 10 percent level ($p<0.10$).

Conclusions and Policy Implications

Factors influencing inequality in rural households are complex. The present study clearly demonstrated that the total income derived from crop production is higher in a diversified cropping system and cultivation of modern varieties of rice alone does not necessarily translate into high total income. Gini-decomposition results support this intuition. It revealed that the contribution of diverse crop production to existing inequality is lowest (only 10 percent) while modern agricultural technology adoption contributes about 29 percent, even though both have an inequality decreasing effect while total income remains unchanged.

Among the socio-economic characteristic variables, education levels of the head of household significantly increase consumption/welfare whereas the number of dependent persons has a doubly disadvantageous effect as it significantly reduces consumption by a large margin. Turning to the impact of land, land ownership significantly increases consumption and is the most dominant positive variable.

In general, it is encouraging to note that factors within the control of household decision making processes, such as education levels and sources of income, particularly from diverse crop and modern variety cultivation and non-agricultural income, reduce inequality in the distribution of income and/or significantly increase consumption/ welfare. Therefore, the inherent disadvantage posed by location and underdeveloped infrastructure in increasing inequality and/or reducing consumption can be somewhat offset by promoting crop diversification and modern agricultural technology diffusion in addition to mass adult literacy improvement. Also, government has an important role to play to improve the factor equalization role of land rental markets because farming is still the dominant source of livelihood in Bangladesh and our results reveal that consumption/welfare are significantly lower for tenants. However, the conventional land reform measure of equalizing land ownership among farmers, which is a common policy suggestion in land scarce economies, is not feasible in the case of Bangladesh because of technical and economic limitations, as well as the political economy of its agrarian structure (Rahman 2010). The key policy thrust here should be to facilitate the operation of the land rental markets instead, as well as to improve ownership of the farm-capital assets that are also essential in farm operations, which is shown to significantly improve consumption.

Therefore, an integrated policy of decentralized crop diversification, incorporating the balanced adoption of modern agricultural technology (e.g., one main season in a crop year cycle), mass adult literacy promotion, tenancy reform to enable land rental market to operate effectively, and rural infrastructure development to promote economic diversification and non-agricultural income, is recommended in programs designed to reduce income inequality and increase consumption/welfare of rural households in Bangladesh.

References

Achia, T.N.O., Wangombe, A., & Khadioli, N. (2010). A logistic regression model to identify key determinants of poverty using Demographic Health Survey data. *European Journal of Social Science*, 13(1), 38–46

Ahmed, R., & Hossain, M. (1990). *Developmental impact of rural infrastructure in Bangladesh* (Research Report No. 83). Washington, DC: International Food Policy Research Institute.

Anyanwu, J. C. (2005). Rural poverty in Nigeria: Profile, determinants and exit paths. *African Development Review*, 17(3), 435–460.

Asadullah, M. N., & Rahman, S. (2009). Farm productivity and efficiency in rural Bangladesh: The role of education revisited. *Applied Economics*, 41(1), 17–33.

Barrett, C. B., Reardon, T. & Webb, P. (2001). Nonfarm income diversification and household livelihood strategies in rural Africa: Concepts, dynamics, and policy implications. *Food Policy,* 26(4), 315–331.

Bangladesh Bank. (2012). *Economic Trends (monthly publications) 2012*. Dhaka: Bangladesh Bank.

Bangladesh Bureau of Statistics (BBS), (2012). *Yearbook of agricultural statistics of Bangladesh, 2012*. Dhaka: Author.

Benson, T., Chamberlin, J. & Rhinehart, I. (2005). An investigation of the spatial determinants of local prevalence of poverty in rural Malawi. *Food Policy*, 30(5-6), 532–500

Davis, J. R. (2004). *The rural non-farm economy, livelihoods and their diversification: Issues and options*. Chatham, UK: Natural Resources Institute, University of Greenwich. Retrieved from: http://www.nri.org/projects/rnfe/papers.htm.

Deininger, K., & Olinte, P. (2001). Rural non-farm employment and income diversification in Columbia. *World Development*, 29(3), 455-465.

Ellis, F. (2000). *Rural livelihoods and diversity in developing countries*. Oxford: Oxford University Press.

Ellis, F. & Freeman, H. A. (2004). *Rural livelihoods and poverty reduction* *policies*. London: Routledge.

Fei, J., Ranis, G. & Kuo, S. (1978). Growth and the family distribution of income by factor components. *Quarterly Journal of Economics*. 92(1), 17–53.

Freebairn, D.K. (1995). Did the Green Revolution concentrate incomes? A quantitative study of research reports. *World Development,* 23(2), 265-279.

Hatlebakk, M. (2012). Regional variation in livelihood strategies in Malawi. *South African Journal of Economics*, 80(1), 62-76.

Hossain, M. (1989). *Green revolution in Bangladesh: Impact on growth and distribution of income*. Dhaka: University Press Ltd.

Hossain, M. & Sen, B. (1992). Rural poverty in Bangladesh: Trends and determinants. *Asian Development Review*, 10(1), 1–34.

Hossain, M., Quasem, M. A., Akash, M. M., & Jabber, M. A. (1990). *Differential impact of modern rice technology: The Bangladesh case*. Dhaka: Bangladesh Institute of Development Studies.

Krishna, A. (2013). The mixed news on poverty. *Current History*, 112(750), 20-25.

Makdissi, P., & Wodon, Q. (2012). Gini decomposition and gini income elasticity under income variability. *Bulletin of Economic Research*, 64(2), 184–191

Mian, A. J. (1978). *A least cost nutritional diet for Bangladesh: An alternative approach to food supply* (Ph.D. Dissertation). Ohio: The Ohio State University.

Ministry of Agriculture. (2008). *Agricultural handbook of Bangladesh, 2007*. Dhaka: Ministry of Agriculture, Government of Bangladesh.

Pyatt, G. (1976). On the interpretation and disaggregation of Gini coefficients. *Economic Journal.* 86(342), 243–255.

Pyatt, G., Chen, C-N., & Fei, J. (1980). The distribution of income by factor components. *Quarterly Journal of Economics*. 95(3), 451–473.

Rahman, S. (1999). The impact of technological change on income distribution and poverty in Bangladesh agriculture: An empirical analysis. *Journal of International Development*, 11(7), 935–955.

Rahman, S. (2009). Micro-determinants of poverty among farming population in Bangladesh. *Outlook on Agriculture*. 38(4), 349-355.

Rahman, S. (2010). Determinants of agricultural land rental market

transactions in Bangladesh. *Land Use Policy*, 27(3), 957–964
Rao, V. M. (1969). Two decompositions of concentration ratio. *Journal of Royal Statistical Society, Series A*. Series A(132): 418 – 25.
Ravallion, M. & Sen, B. (1996). When methods matter: Monitoring poverty in Bangladesh. *Economic Development and Cultural Change*, 44(4), 761 – 792.
Ravallion, M., & Wodon, Q.T. (1999). Poor areas, or only poor people? *Journal of Regional Science*, 39(4), 689–711
Smith, D.R. Gordon, A., Meadows, K., & Zwick, K. (2001). Livelihood diversification in Uganda: Patterns and determinants across two rural districts. *Food Policy*, 26, 421-435.
Stata Corp, (2010). *Stata Statistical Software: Release 10.0.* College Station, Texas: Author.
Thapa, G., Otsuka, K., & Barker, R. (1992). Effect of modern rice varieties and irrigation on household income distribution in Nepalese villages. *Agricultural Economics*. 7(3-4), 245–65.
Wodon, Q. T. (1997). Food energy intake and cost of basic needs: measuring poverty in Bangladesh. *Journal of Development Studies*. 34(2), 66–101.
Wodon, Q. T. 2000. *Microdeterminants of Consumption, Poverty, Growth, and Inequality in Bangladesh*. Applied Economics, 32(10), 1337–1352.
Yao, S. 1997. Decomposition of Gini coefficient by income factors: A new approach and application. *Applied Economics Letters*. 4(1), 27–31.

Appendix

Components of Household Income

The disaggregation of total family income into the following components provides a first-hand picture of sources of income:

1. Income from crop production (CROPI)
2. Income from livestock (LIVEI)
3. Income from fisheries (FISHI)
4. Income from land leased-out/rented-out (LEASEI)
5. Income from wage (WAGEI)
6. Income from business and miscellaneous sources (BUSI)
7. Total agricultural income (AGI) = CROPI + LIVEI + FISHI + LEASEI
8. Total non-agricultural income (NAGI) = WAGEI + BUSI
9. Total household income (INC) = AGI + NAGI

Derivation of Income

Income derived from crop production (CROPI) is straightforward. As the present study covers information on all types of crops produced by the households in one year, so the total income from producing various crops are computed directly after deduction of all input costs including purchased and family supplied items. Costs of family supplied inputs were imputed with the respective market prices as appropriate. The income is net income from crop production.

Income from livestock sources are estimated from direct questions to the respondents on various products and by-products produced from livestock resources, such as from milk, meat, egg, sale, value of consumed product, etc. Also, information on weekly expenditure on livestock raising is collected which is then multiplied by 52 to arrive at an annual expenditure and deducted from total gross income to yield net income from livestock.

Incomes from fisheries resources are estimated from direct questions on costs and returns of fish production in one year. Costs include excavation, liming, fertilizing, feeding, renting (if multiple owned) and harvesting costs. Incomes include revenue from sale of harvest, imputed value of fish consumed by the family and value of stock in the pond. The total cost is then deducted from gross income to yield net income from fisheries.

Income from all other categories are estimated from direct questions on type of activities, in which individual working members of the household are involved for one week preceding the day of survey, number of days worked and income earned from these activities. This weekly income derived from various sources is then multiplied by 52 to arrive at the annual income.

It should be noted that though such computation is highly subjective, a cross-examination of annual expenditure incurred by the household (based on similar method which is reported in lower panel of Table 2) and the derived total income revealed a discrepancy of about 10–15 percent only.